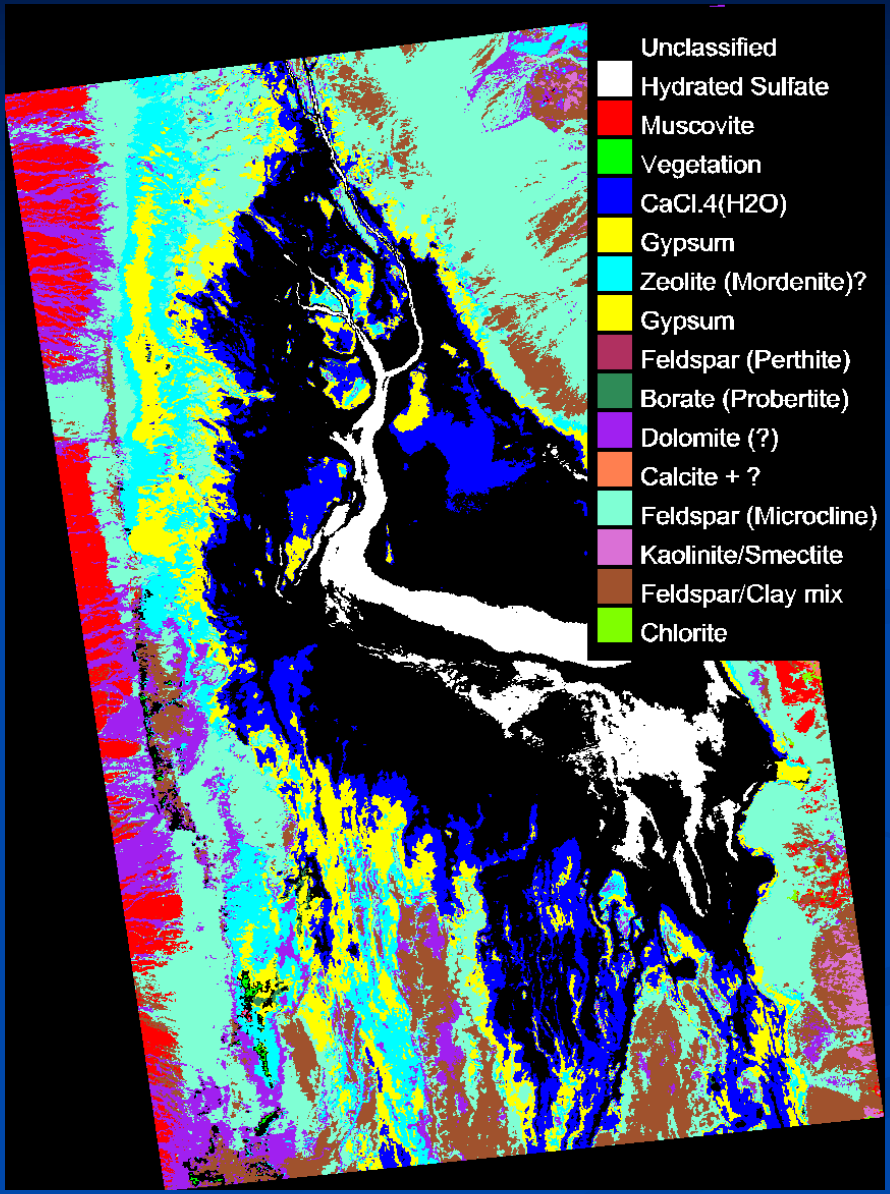
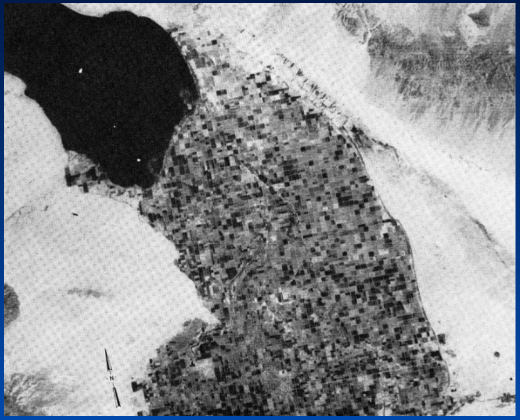
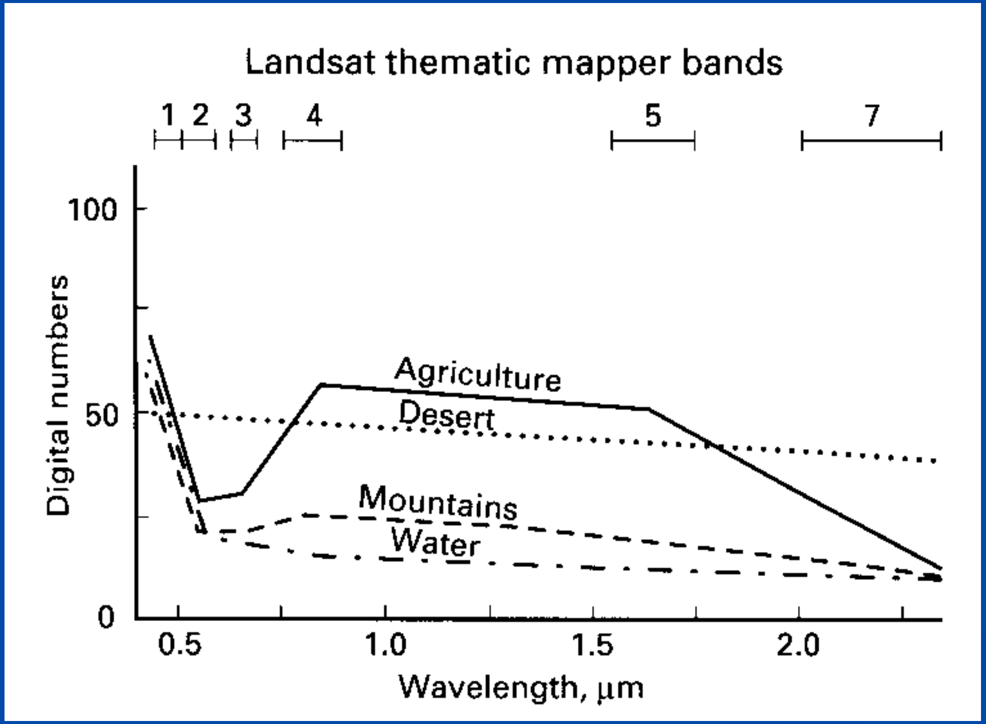
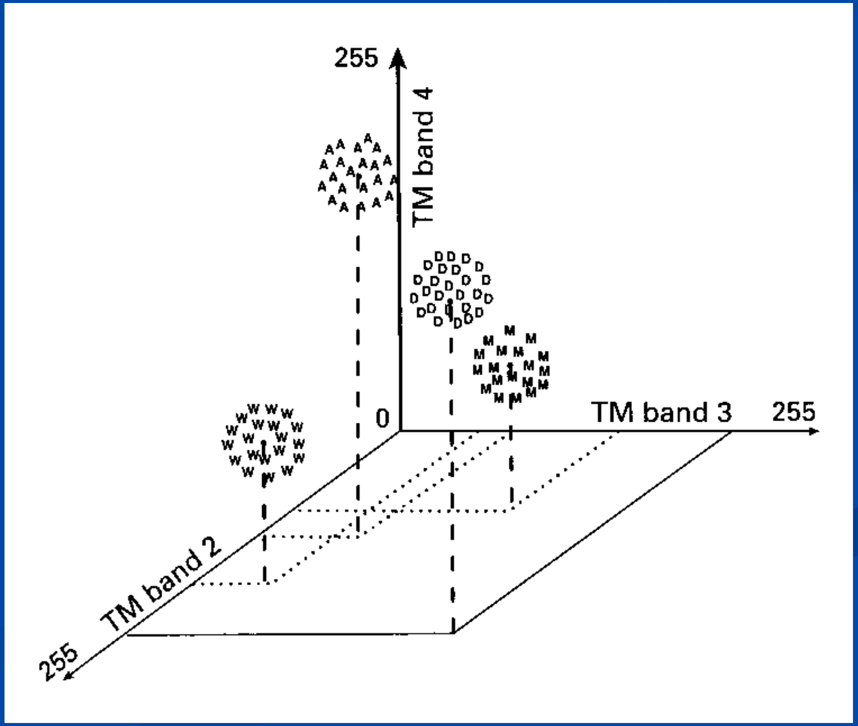
Spectral Classification



Spectral Classification



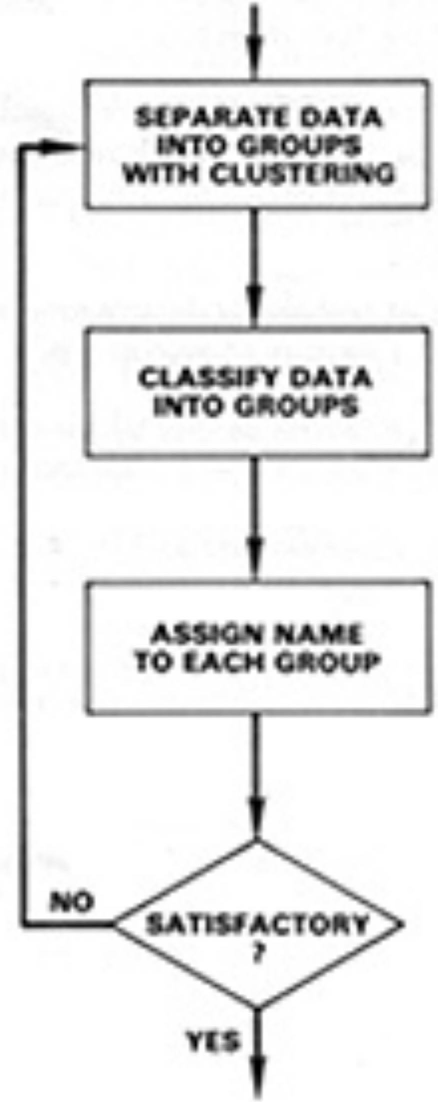




Supervised versus Unsupervised Classification

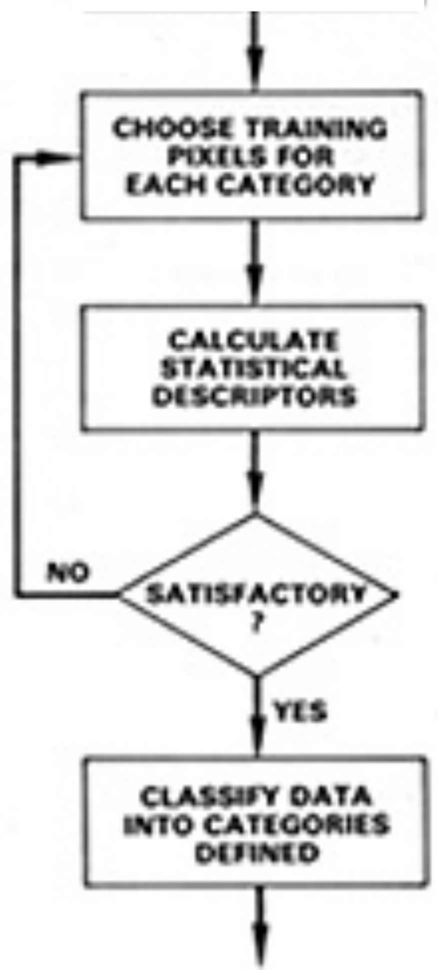
- "Unsupervised" – Classes are determined by the computer. Also referred to as "clustering"
- "Supervised" – Classes are specified by analyst, typically via extraction of spectra from training areas in the scene.

UNSUPERVISED CLASSIFICATION



A

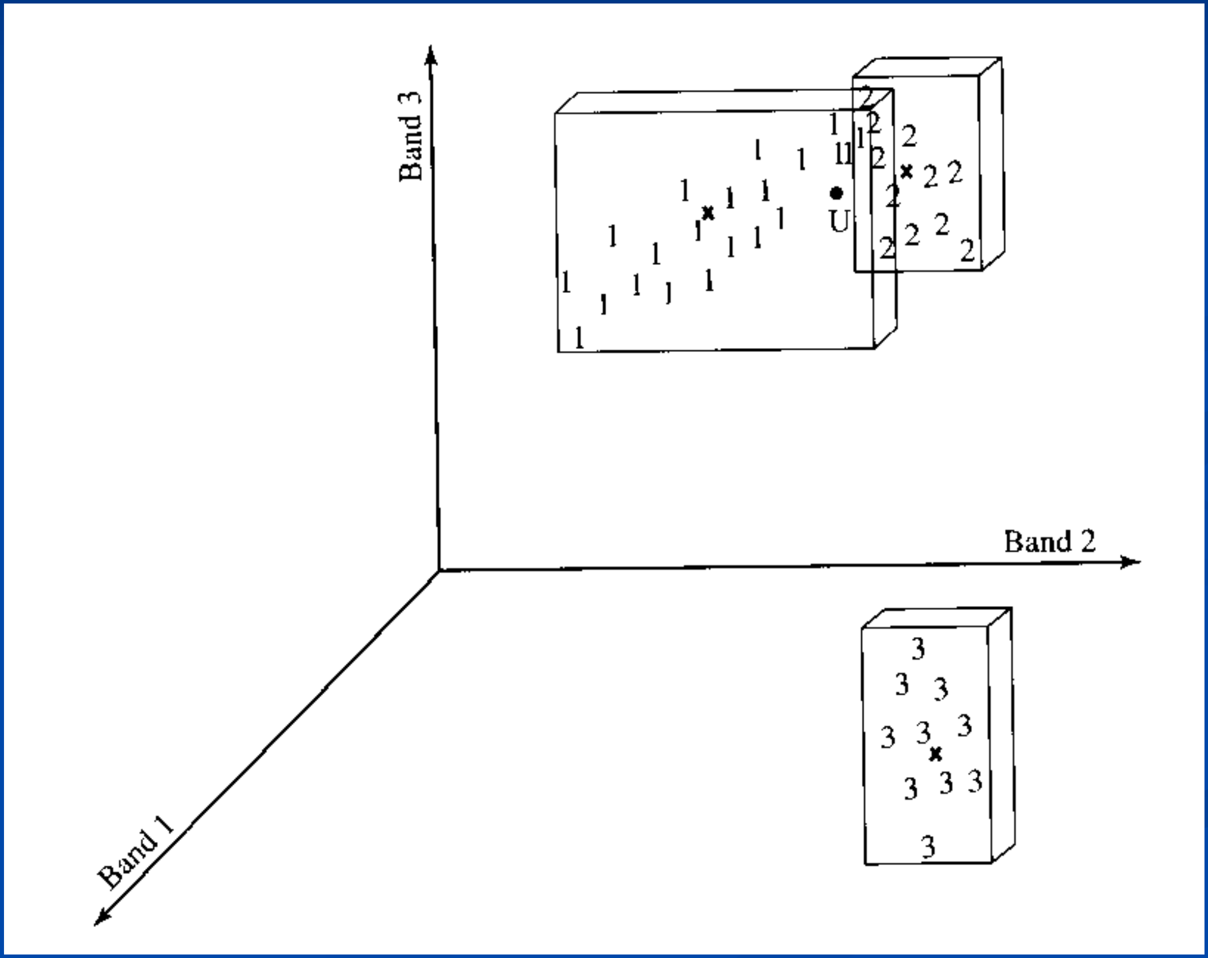
SUPERVISED CLASSIFICATION



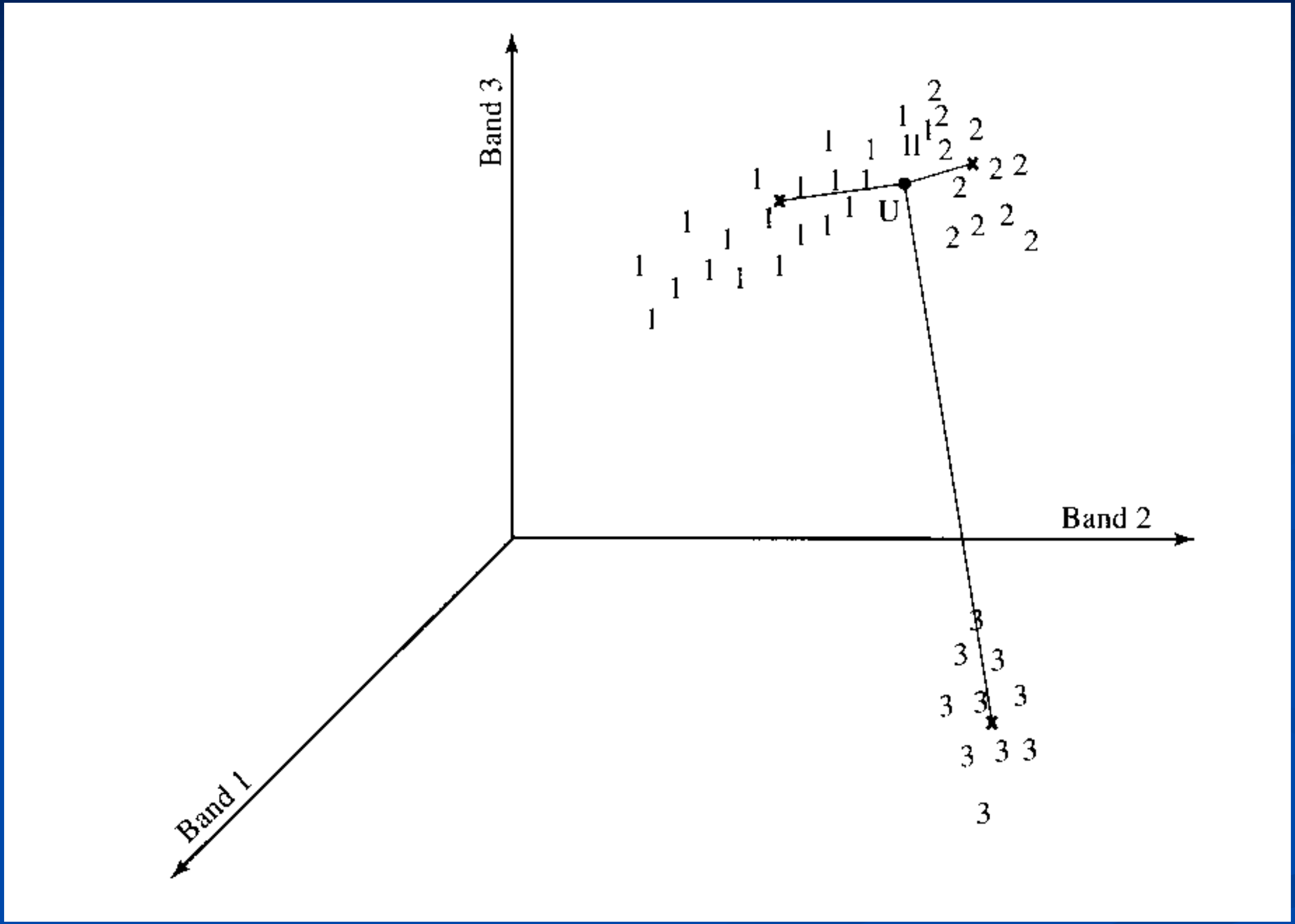
B

Supervised Classifications
(all available in ENVI!)

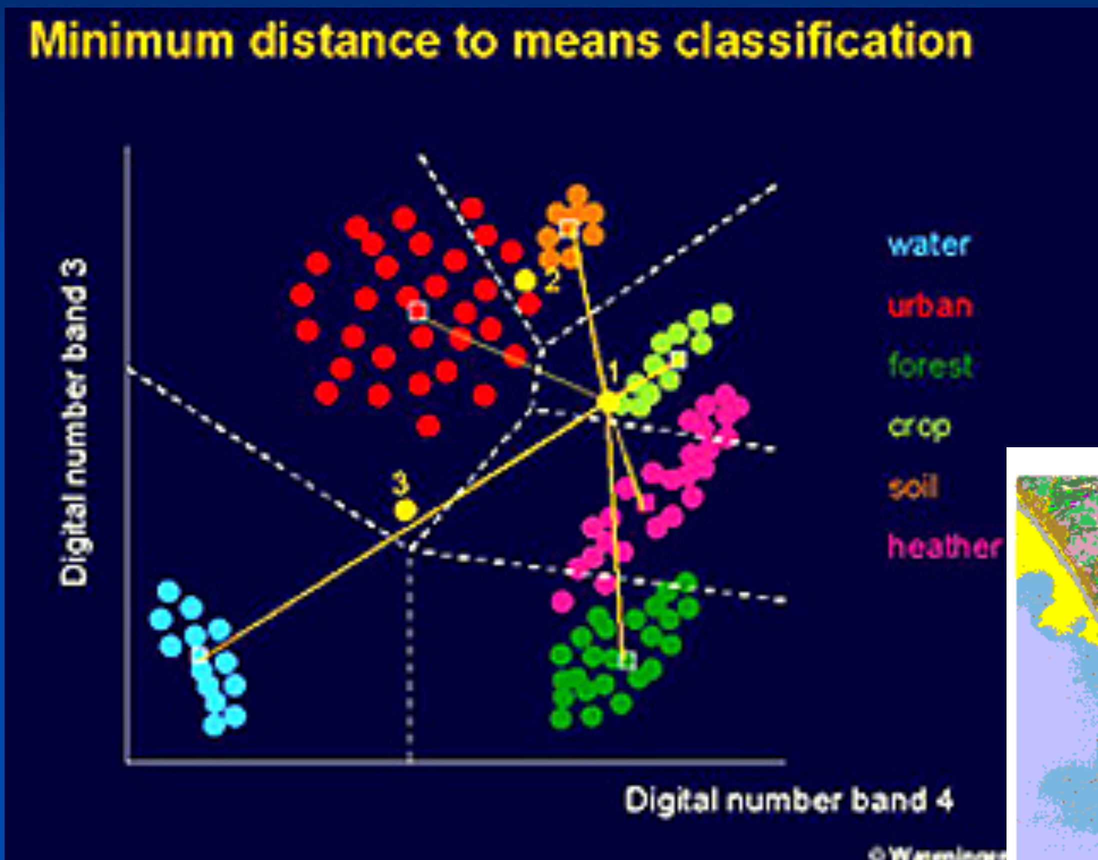
Parallelepiped

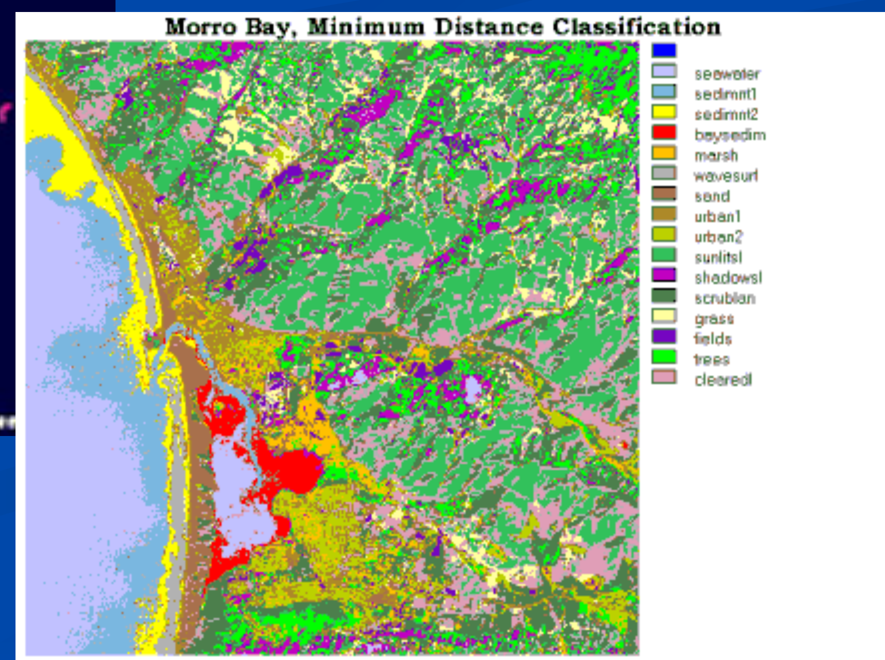


Minimum Distance

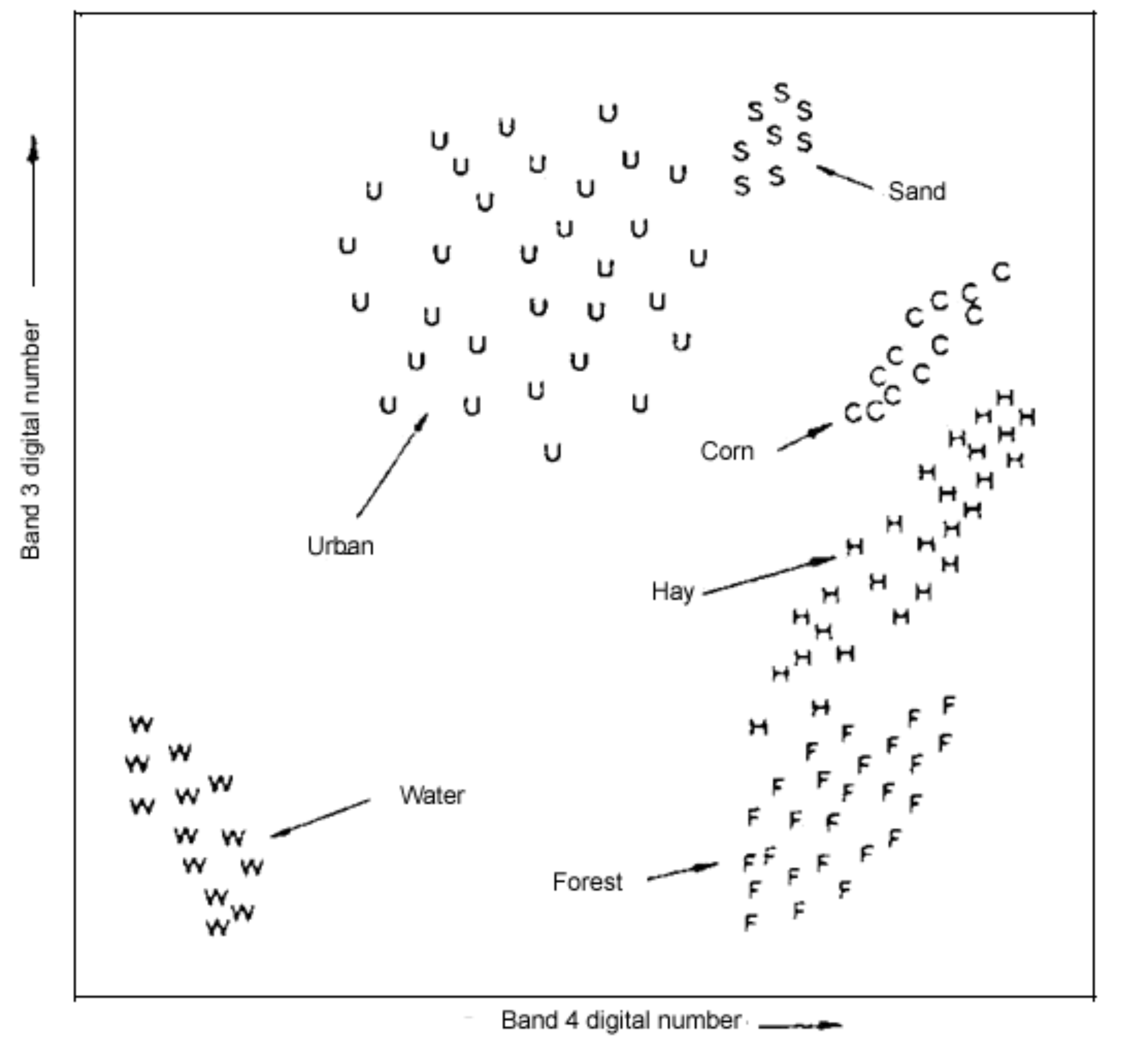


Minimum Distance Method

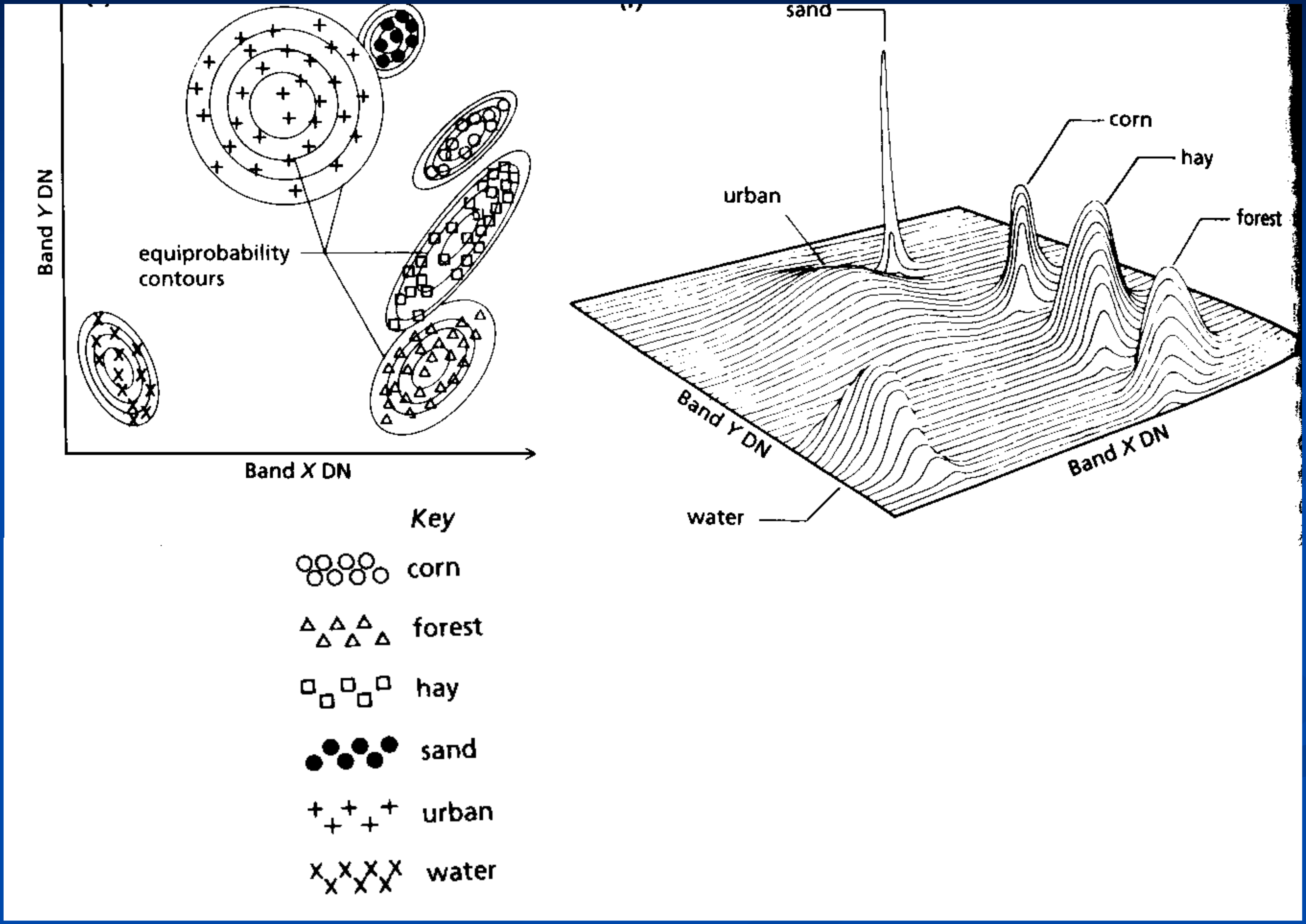




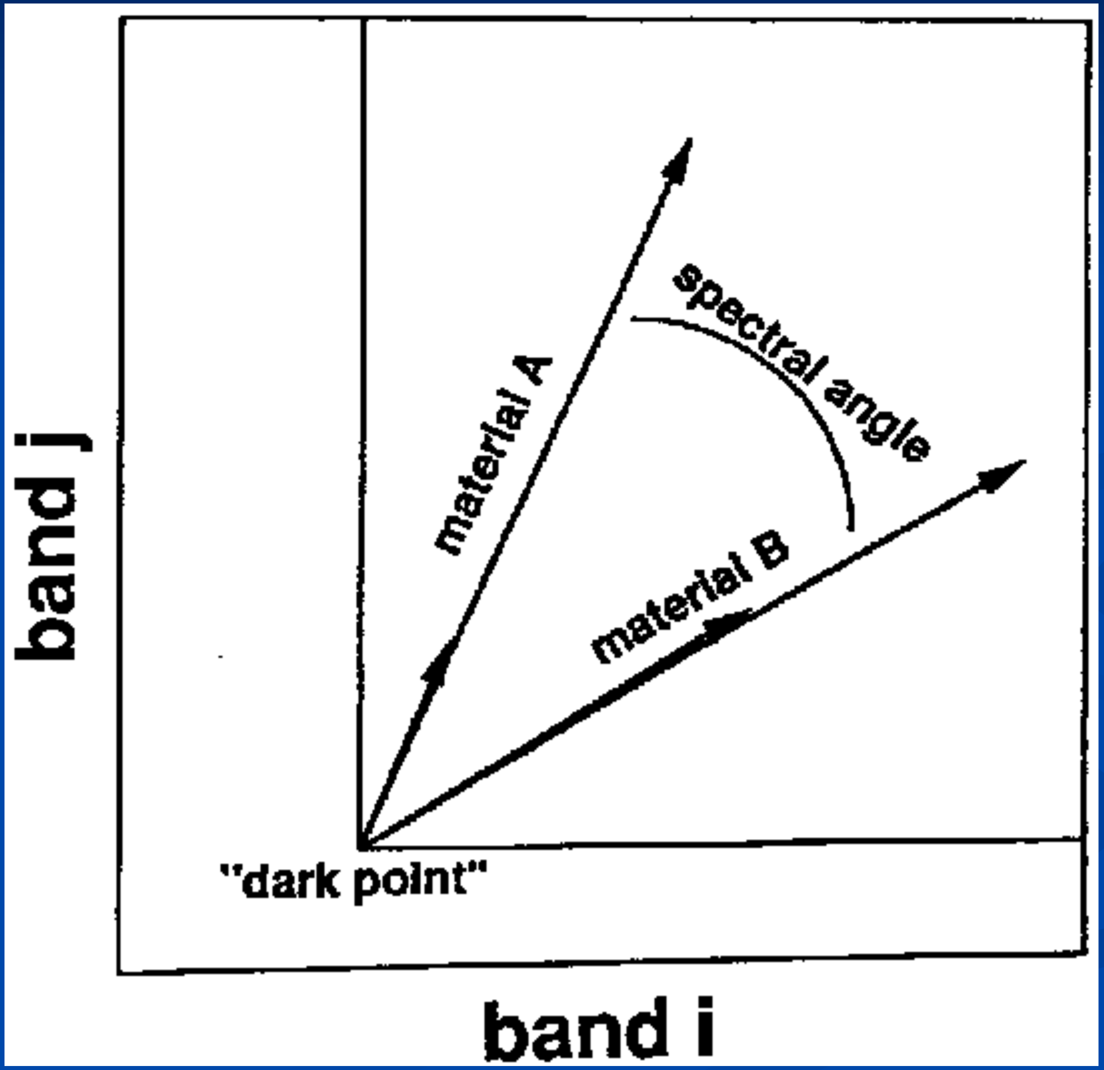
Maximum Likelihood



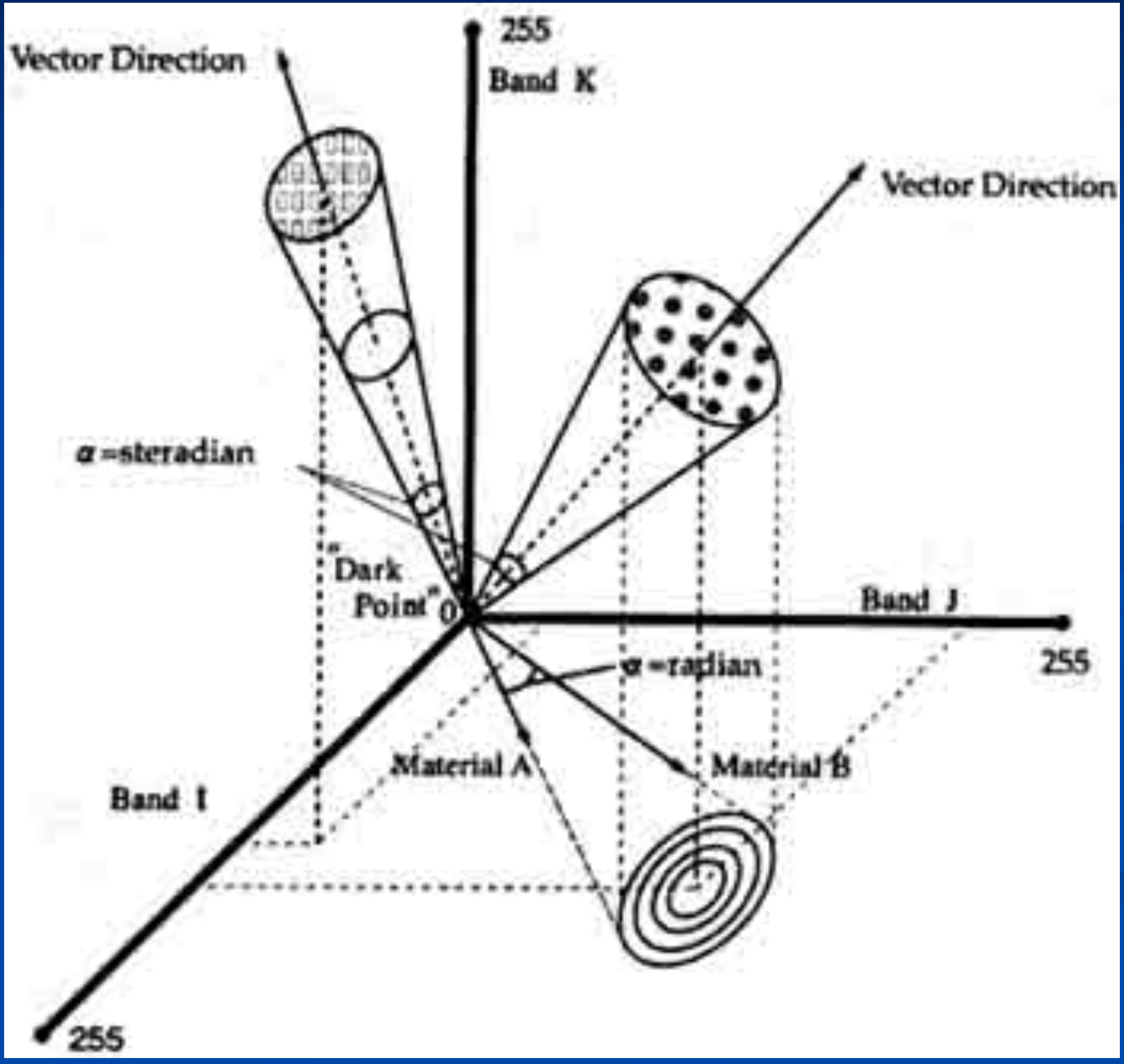
Maximum Likelihood



Spectral Angle Mapper



Spectral Angle Mapper

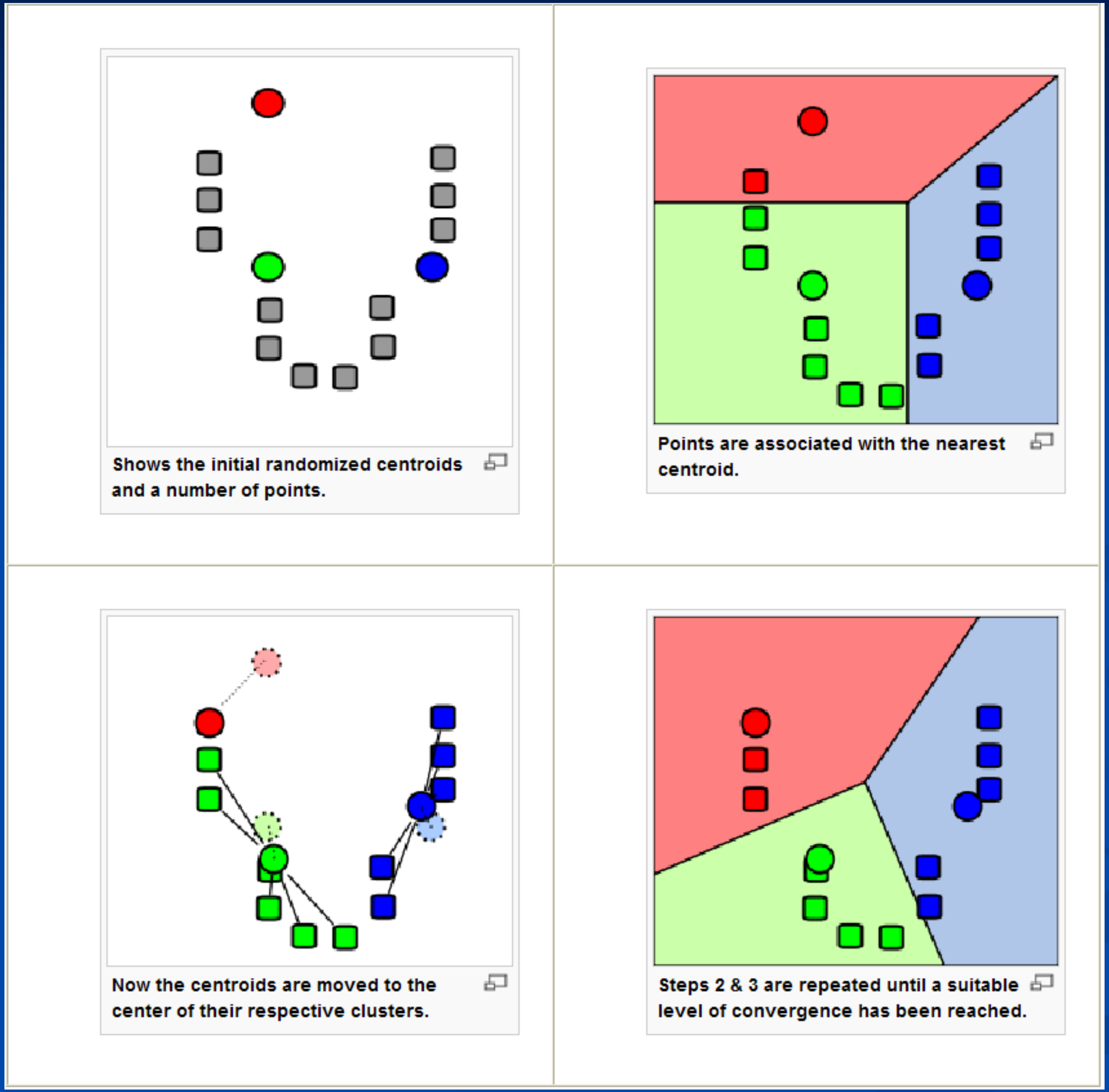


Unsupervised Techniques: K-Means

- User specifies # of classes. Algorithm first assigns randomly distributed class centers in n-D space, clusters pixels according to min. distance. Next iteration, finds mean coordinates of clusters, uses these locations as new class centers and re-clusters by distance. Continues until means move less than a specified threshold between subsequent iterations.

Most useful when you know the number of spectral units in a scene a priori, but don't necessarily know where they fall within the scene (so supervised techniques aren't possible).

K-Means



Demo:

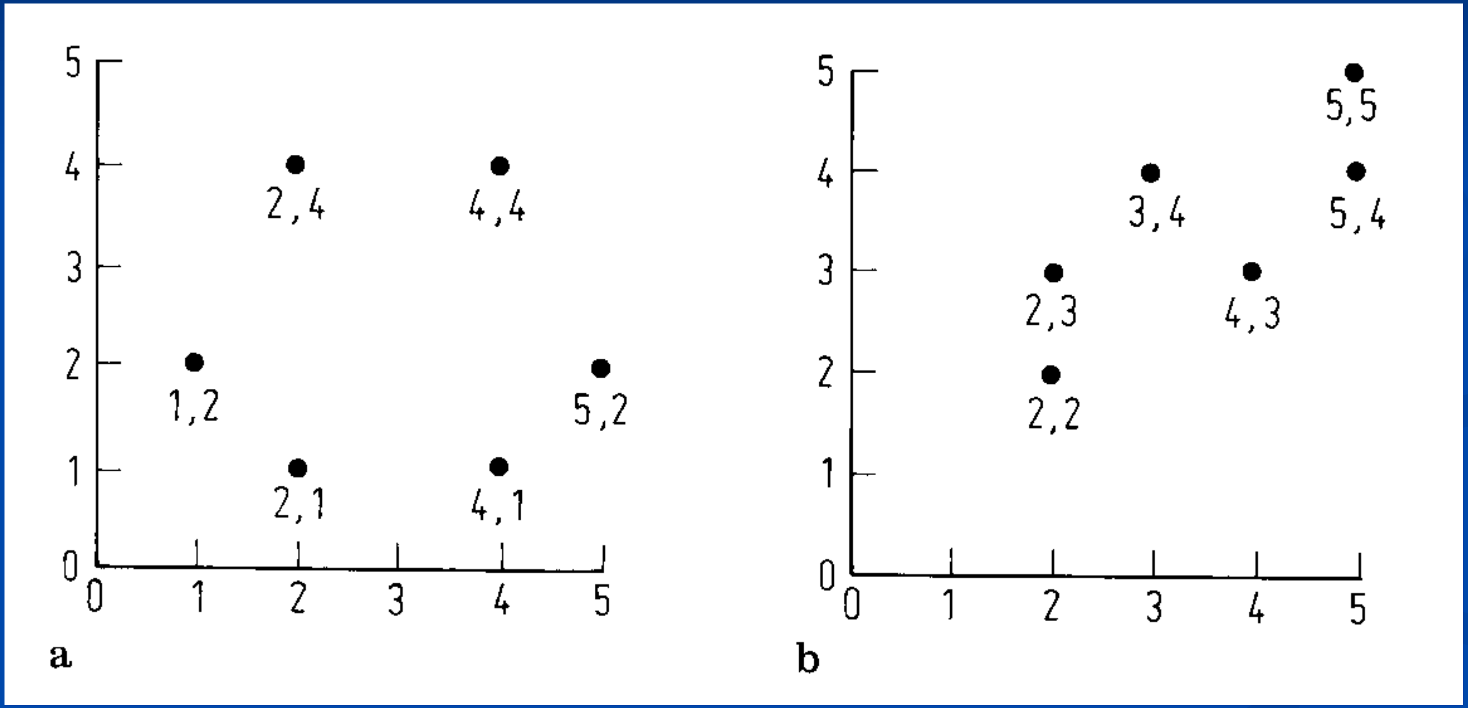
http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletKM.html

Unsupervised Techniques: Isodata

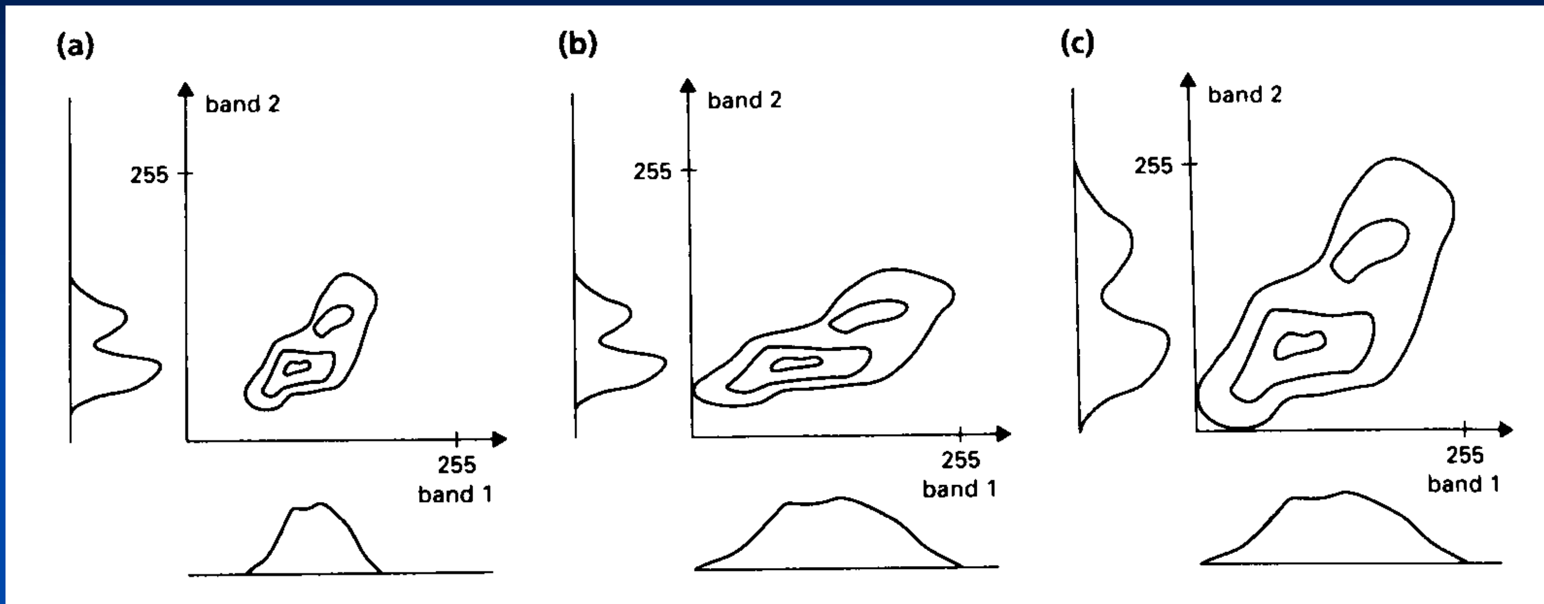
- Similar to K-means, except user doesn't need to specify number of classes. Algorithm starts with randomly spaced trial classes, calculates minimum distances to cluster all pixels in the scene. Before next iteration, algorithm looks at the statistics of each class to see if any should be split, merged, or deleted. Iterations continue until number of pixels in each class changes less than some threshold between iterations.

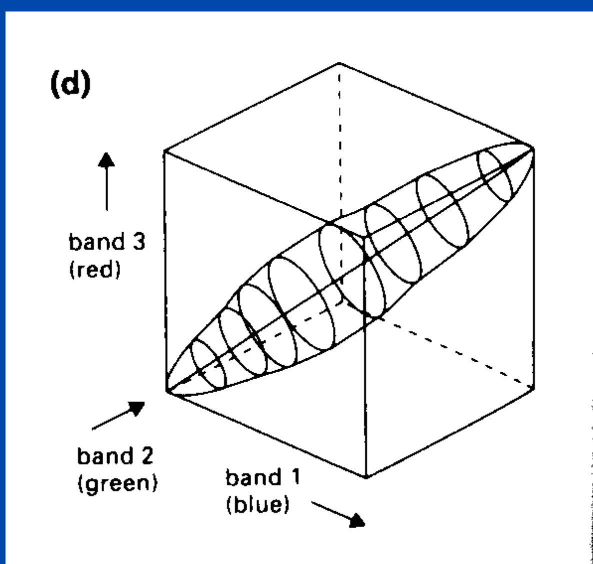
Most useful when you don't have a clue how many spectral units are likely to be present in a scene.

Correlated vs. Uncorrelated Data



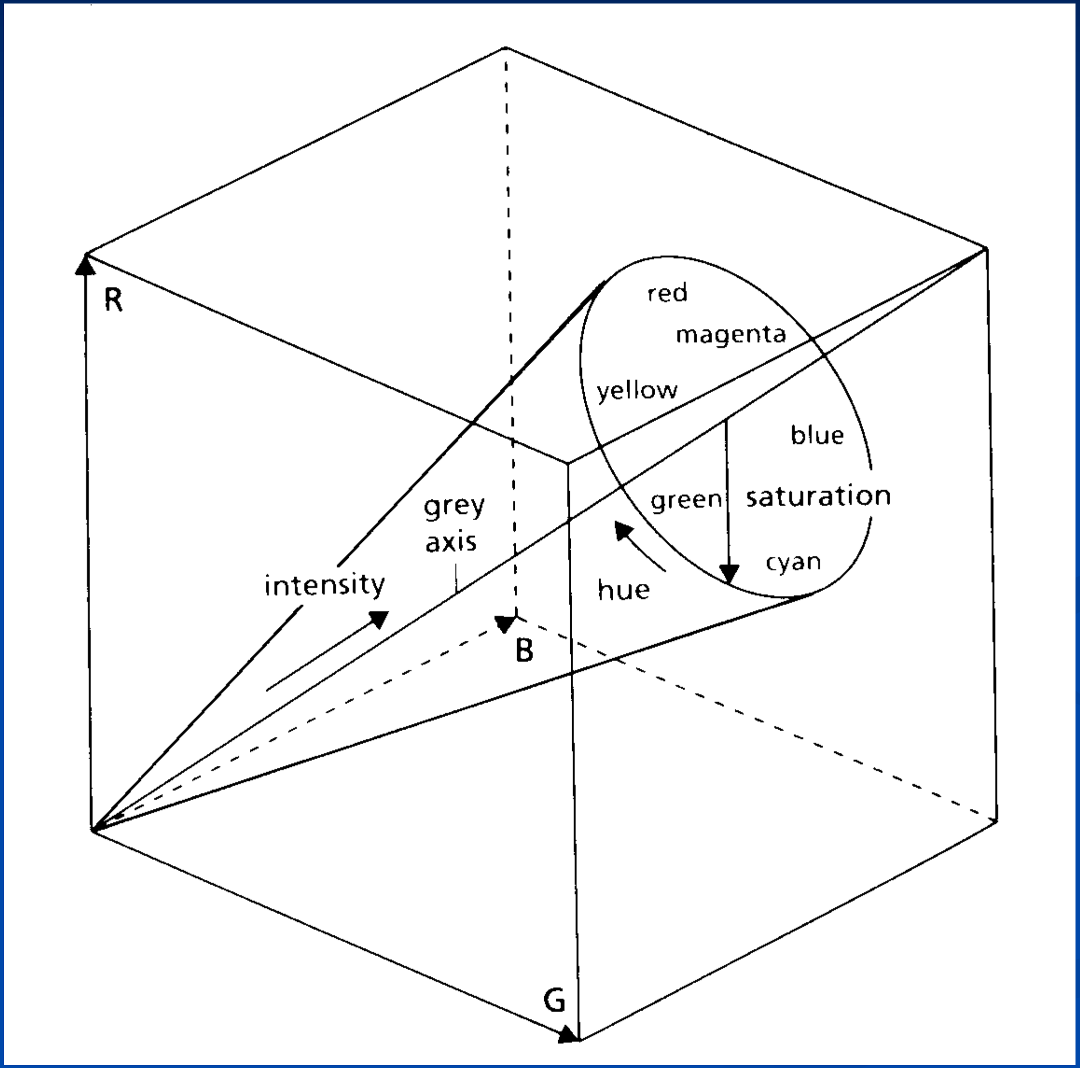
3-Band Correlations in RGB





Data only occupy a small fraction of the total colors available for display.

Intensity, Saturation, and Hue



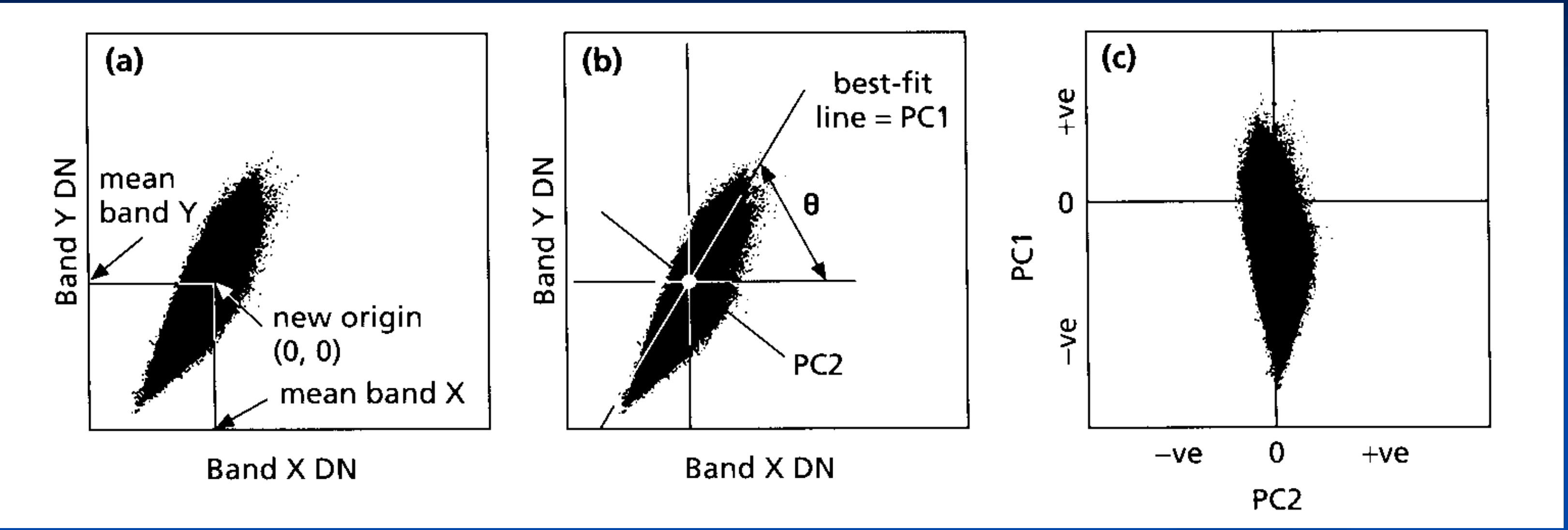
Most of the compositional information is in hue and saturation.

- An “HIS stretch” usually involves converting RGB coordinates for pixels into measures of hue, intensity, and saturation. Intensity and saturation can be stretched to more completely fill color space.
- Often, another higher spatial resolution, mono- or pan-chromatic band is used to replace the original intensity data. The lower resolution multispectral data are used to provide hue and saturation in the merged (or “fused”) output image. Called “Pan-sharpening.”

Principal Component Analysis (PCA)

- Multispectral, and especially hyperspectral data have more information from more wavelengths than our brains can process!
- Often, one band is highly correlated with another
- PCA offers a way to reduce the inherent "dimensionality" of a multi- or hyperspectral dataset into the smallest number of independent dimensions
- Makes contrast enhancement of different classes much better

Principal Component Analysis (PCA)



1. Move origin of coordinate system to center (mean) of data cloud.
2. Find a rotation of axes that maximizes the variance of the data along the new orientations of the axes.
3. Stretch the data along the new axes to fill the color space – points are no longer correlated.

PCA Terminology

- Eigenvector: Describes the shift and orientation of the new axes. For n input bands, you get n output bands with n associated eigenvectors

- Eigenvalue: Describes the magnitude of the variance along the new axes (prior to stretching). There is one eigenvalue for each axis.

PCA Advantages

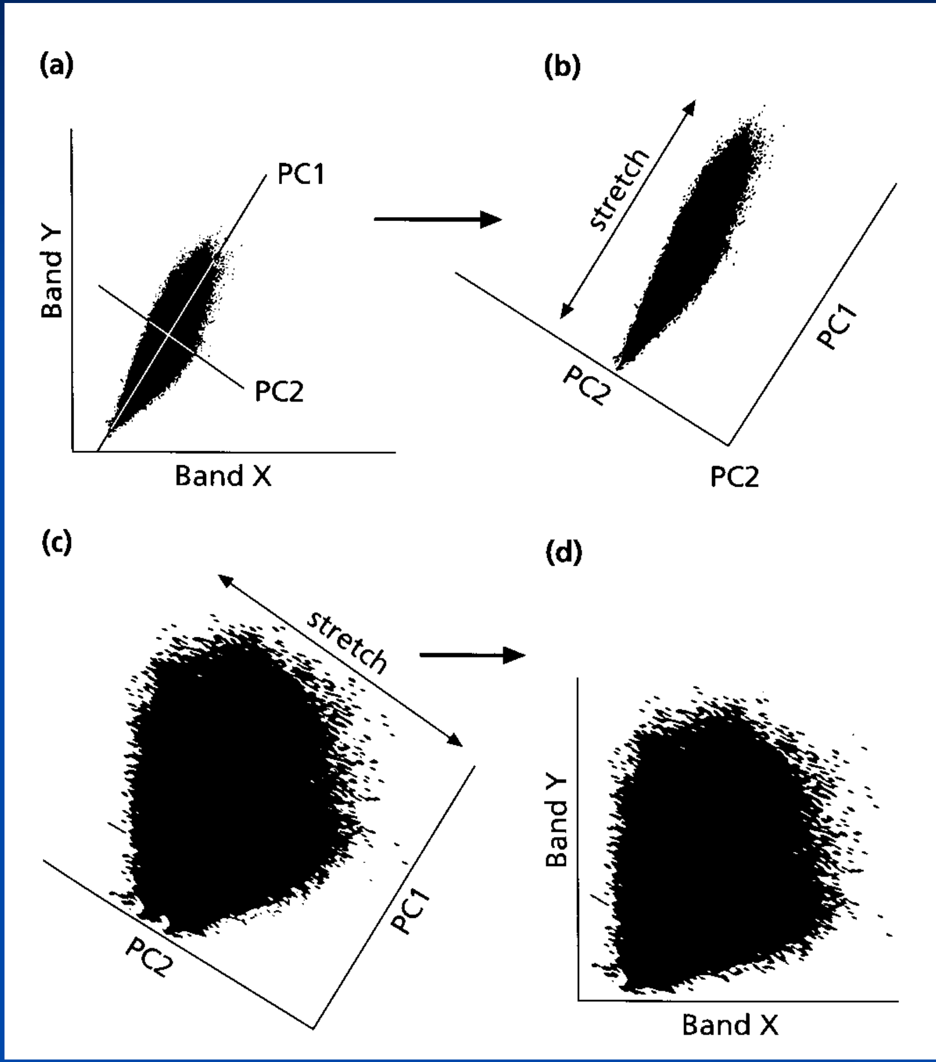
- PCA analysis can simultaneously consider all input bands.
- Has the effect of reducing the “dimensionality” of the data (fewer # of bands contain most of the information) because higher-order axes don’t contain as much independent (uncorrelated) information.
- More completely fills the available color space when PCA bands are displayed in RGB triplets

PCA Disadvantages

- Can be difficult to understand PCA bands in terms of composition – no one-to-one correspondence between a particular PCA band and any one input band.

Typically, PCA bands are used to map the spectral/ compositional units in a scene. Once the pixels belonging to a particular spectral unit have been identified, compositional identifications are made using spectra for those pixels extracted from the original input pixels (pre-PCA).

Decorrelation Stretching



After performing a PCA rotation and stretching the data, the axes are rotated back to their original (input) orientations.

Preserves original sense of "color."